

The Structure and Complexity of Credal Semantics

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- 1 Credal semantics: definition.
- 2 The structure of credal semantics.
- 3 Inference and query complexity.

Probabilistic logic programs

- A probabilistic logic program is a pair $\langle \mathbf{P}, \mathbf{PF} \rangle$ where
 - \mathbf{P} is a normal logic program (no functions) and
 - \mathbf{PF} is a set of probabilistic facts.

- Predicate r , atom $r(t_1, \dots, t_k)$, rule

$$A_0 :- A_1, \dots, A_m, \mathbf{not} A_{m+1}, \dots, \mathbf{not} A_n.$$

- A_0 is the head, the right hand side is the body.
- A rule without a body is a *fact*.
- A program without **not** is *definite*.
- Atom without logical variables is a *ground atom*.
- A program without logical variables is *propositional*.

- A probabilistic fact is a fact associated with a probability:

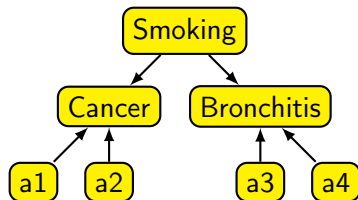
$$\mathbb{P}(A) = \alpha.$$

- Probabilistic facts are assumed independent.

Example: the Bayesian network Asia

- Predicates smoking, cancer, and bronchitis.
- Probabilistic logic program (ProbLog notation):

```
0.5 :: smoking.  
cancer :- smoking, a1.  
cancer :- not smoking, a2.  
bronchitis :- smoking, a3.  
bronchitis :- not smoking, a4.  
0.1 :: a1.      0.01 :: a2.  
0.6 :: a3.      0.3 :: a4.
```



Acyclic programs (acyclic dependency graphs)

- For each total choice of probabilistic facts, we have an acyclic logic program (with the usual semantics).
- Hence the semantics of an acyclic probabilistic logic program is a single distribution — a Bayesian network (Poole (1993)).

Stratified programs:

- ... the grounded dependency graph has no cycle containing a *negative* edge.
- Example:

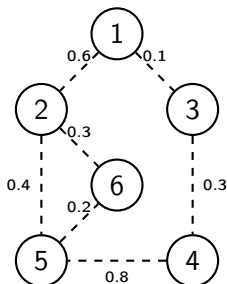
```
path(X, Y) :- edge(X, Y).  
path(X, Y) :- edge(X, Y), path(X, Y).
```

```
0.6 :: edge(1, 2).  0.1 :: edge(1, 3).  
0.4 :: edge(2, 5).  0.3 :: edge(2, 6).  
0.3 :: edge(3, 4).  0.8 :: edge(4, 5).  
0.2 :: edge(5, 6).
```

A random graph

```
path(X, Y) :- edge(X, Y).  
path(X, Y) :- edge(X, Y), path(X, Y).
```

```
0.6 :: edge(1, 2).  0.1 :: edge(1, 3).  
0.4 :: edge(2, 5).  0.3 :: edge(2, 6).  
0.3 :: edge(3, 4).  0.8 :: edge(4, 5).  
0.2 :: edge(5, 6).
```



Semantics of stratified probabilistic logic programs

- For each total choice of probabilistic facts, we have a stratified logic program.
- Hence the semantics of a stratified probabilistic logic program is a single distribution (with the usual semantics).

- The semantics of acyclic and stratified programs is uncontroversial: just take the unique stable model (= answer set = well-founded model).
- To recap:
 - Consider logic program \mathbf{P} .
 - For some interpretation \mathcal{I} , take the reduct $\mathbf{P}^{\mathcal{I}}$:
 - Ground \mathbf{P} .
 - Remove rules with subgoal **not** A and $A \in \mathcal{I}$.
 - Remove subgoals **not** A from remaining rules.
 - Interpretation \mathcal{I} is stable model if \mathcal{I} is the minimal model of $\mathbf{P}^{\mathcal{I}}$.

Non-stratified program (cycle with negative edge)

- Non-stratified program may have more than one stable model.

The Dilbert example

$\text{single}(X) :- \text{man}(X), \text{not husband}(X).$

$\text{husband}(X) :- \text{man}(X), \text{not single}(X).$

$0.9 :: \text{man}(\text{dilbert}).$

- $\text{man}(\text{dilbert})$ is false: a unique stable model s_1 .
- $\text{man}(\text{dilbert})$ is true: there are two stable models,

$s_2 = \{\text{husband}(\text{dilbert}) = \text{true}, \text{single}(\text{dilbert}) = \text{false}\},$

and

$s_3 = \{\text{husband}(\text{dilbert}) = \text{false}, \text{single}(\text{dilbert}) = \text{true}\}.$

What could be the semantics of a non-stratified program?

- Probabilities over well-founded models:
 - Sato, Kameya and Zhou (2005),
 - Hadjichristodolou and Warren (2012).
 - Riguzzi (2015).
- Proposal by Lukasiewicz (2005):
informally, take the set of every possible probability distributions that satisfy the rules and (probabilistic) facts.

The Dilbert example

$\text{single}(X) :- \text{man}(X), \text{not husband}(X).$

$\text{husband}(X) :- \text{man}(X), \text{not single}(X).$

$0.9 :: \text{man}(\text{dilbert}).$

- A probability model:
 $\mathbb{P}(s_1) = 0.1$ and $\mathbb{P}(s_2) = 0.9$ hence $\mathbb{P}(s_3) = 0.$
- Another one: $\mathbb{P}(s_1) = 0.1$ and $\mathbb{P}(s_3) = 0.9$ hence $\mathbb{P}(s_2) = 0.$
- Actually, take any $\gamma \in [0, 1]$:

$$\mathbb{P}(s_1) = 0.1, \quad \mathbb{P}(s_2) = 0.9\gamma, \quad \mathbb{P}(s_3) = 0.9(1 - \gamma).$$

- Given $\langle \mathbf{P}, \mathbf{PF} \rangle$:
 - A probability model is a probability measure over stable models of the program, such that all probabilistic facts are respected and independent.
 - The set of all probability models is the semantics of the probabilistic logic program.

- Lukasiewicz calls this the “answer-set semantics”.
 - More general than answer set programming.
 - Different from answer set semantics (probabilities).
 - We prefer *credal semantics*.
 - Note: another recent semantics based on credal sets by Michels et al. (2015).

An example: graph coloring

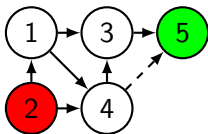
```
coloredBy(V, red) :- not coloredBy(V, yellow), not coloredBy(V, green), vertex(V).  
coloredBy(V, yellow) :- not coloredBy(V, red), not coloredBy(V, green), vertex(V).  
coloredBy(V, green) :- not coloredBy(V, red), not coloredBy(V, yellow), vertex(V).  
noClash :- not noClash, edge(V, U), coloredBy(V, C), coloredBy(U, C).
```

```
vertex(1). vertex(2). vertex(3). vertex(4). vertex(5).
```

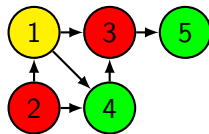
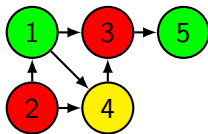
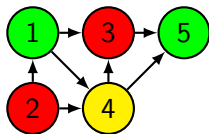
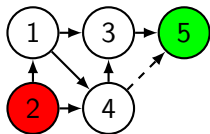
```
coloredBy(2, red). coloredBy(5, green).
```

```
0.5 :: edge(4, 5).
```

```
edge(1, 3). edge(1, 4). edge(2, 1). edge(2, 4). edge(3, 5). edge(4, 3).
```



Inferences

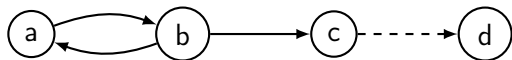


- $\underline{\mathbb{P}}(\text{coloredBy}(1, \text{yellow})) = 0$ and $\overline{\mathbb{P}}(\text{coloredBy}(1, \text{yellow})) = 1/2$.
- $\underline{\mathbb{P}}(\text{coloredBy}(4, \text{yellow})) = 1/2$ and $\overline{\mathbb{P}}(\text{coloredBy}(4, \text{yellow})) = 1$.
- $\underline{\mathbb{P}}(\text{coloredBy}(3, \text{yellow})) = \overline{\mathbb{P}}(\text{coloredBy}(3, \text{yellow})) = 1$.

In the paper: yet another example...

$\text{wins}(X) :- \text{move}(X, Y), \text{not wins}(Y).$

$\text{move}(a, b). \text{move}(b, a). \text{move}(b, c). 0.3 :: \text{move}(c, d).$



- $\text{move}(c, d)$ is false: unique stable model (where $\text{wins}(b)$ is the only winning position);
- otherwise, there are two stable models
 - $\text{wins}(c)$ is true in both of them;
 - $\text{wins}(a)$ is true in one,
 - $\text{wins}(b)$ is true in the other).
- $\underline{\mathbb{P}}(\text{wins}(a)) = 0.0$ and $\overline{\mathbb{P}}(\text{wins}(a)) = 0.3$;
 $\underline{\mathbb{P}}(\text{wins}(b)) = 0.7$ and $\overline{\mathbb{P}}(\text{wins}(b)) = 1.0$;
 $\underline{\mathbb{P}}(\text{wins}(c)) = 0.3$ and $\overline{\mathbb{P}}(\text{wins}(c)) = 0.3$.

A final example

- If the barber shaves every villager who does not shave himself, does the barber shave himself?
- The program

```
shaves( $X$ ,  $Y$ ) :- barber( $X$ ), villager( $Y$ ), not shaves( $Y$ ,  $Y$ ).  
0.5 :: barber(bob).      0.5 :: villager(bob).
```

does not have a stable model.

Theorem

Given a consistent probabilistic logic program, its credal semantics is a set of probability measures that dominate an infinitely monotone Choquet capacity.

- Infinitely monotone Choquet capacity:
belief function, random set...
- Properties:
 - $\underline{\mathbb{P}}(\Omega) = 1 - \underline{\mathbb{P}}(\emptyset) = 1$;
 - for any A_1, \dots, A_n in the algebra,
$$\underline{\mathbb{P}}(\cup_i A_i) \geq \sum_{J \subseteq \{1, \dots, n\}} (-1)^{|J|+1} \underline{\mathbb{P}}(\cap_{j \in J} A_j).$$

Some consequences...

- Credal semantics is a closed and convex set of probability measures.
- We have:

$$\underline{\mathbb{P}}(A) = \sum_{\theta \in \Theta: \Gamma(\theta) \subseteq A} \mathbb{P}(\theta), \quad (\text{cautious inference}),$$

$$\overline{\mathbb{P}}(A) = \sum_{\theta \in \Theta: \Gamma(\theta) \cap A \neq \emptyset} \mathbb{P}(\theta), \quad (\text{brave inference}),$$

$$\underline{\mathbb{P}}(A|B) = \frac{\underline{\mathbb{P}}(A \cap B)}{\underline{\mathbb{P}}(A \cap B) + \overline{\mathbb{P}}(A^c \cap B)},$$

$$\overline{\mathbb{P}}(A|B) = \frac{\overline{\mathbb{P}}(A \cap B)}{\overline{\mathbb{P}}(A \cap B) + \underline{\mathbb{P}}(A^c \cap B)}.$$

- Inference: computing $\underline{\mathbb{P}}(\mathbf{Q})$ for a set of truth assignments \mathbf{Q} .
- An algorithm (Cali et al. (2008)):
 - **Given** a plp $\langle \mathbf{P}, \mathbf{PF} \rangle$ and \mathbf{Q} , initialize a and b with 0.
 - For each total choice θ of probabilistic facts, compute the set S of all stable models of $\mathbf{P} \cup \mathbf{PF}^{\downarrow\theta}$, and:
 - if \mathbf{Q} is true in every stable model in S , then $a \leftarrow a + \mathbb{P}(C)$;
 - if \mathbf{Q} is true in some stable model of S , then $b \leftarrow b + \mathbb{P}(C)$.
 - **Return** a and b (the value of a is $\underline{\mathbb{P}}(\mathbf{Q})$, the value of b is $\overline{\mathbb{P}}(\mathbf{Q})$).

The complexity of inference

Theorem (assume programs are consistent):

Inferential complexity is $\#NP$ -equivalent for propositional prob. programs, and $\#P$ -equivalent when restricted to stratified propositional prob. programs.

For prob. programs where all predicates have a bound on arity, inferential complexity is $\#NP^{NP}$ -equivalent, and $\#NP$ -equivalent when restricted to stratified programs.

(Counting class $\#C$: class of problems solved by a nondeterministic counting polynomial-time Turing machine with oracle C .)

- Query complexity: the complexity of computing $\mathbb{P}(\mathbf{Q})$ when the input is \mathbf{Q} , and the program is fixed.

Theorem (assume programs are consistent):

Query complexity is $\#P$ -hard and in $\#NP$; when restricted to stratified programs, it is $\#P$ -equivalent.

A summary

	Inferential	Query
Acyclic propositional	#P	—
Acyclic relational (arity-bounded)	#NP	#P
Stratified propositional	#P	—
Stratified relational (arity-bounded)	#NP	#P
Non-stratified propositional	#NP	—
Non-stratified relational (arity-bounded)	#NP ^{NP}	∈ #NP
Non-stratified propositional WELL-FOUNDED	#P	—
Non-stratified relational (arity-bounded) WF	#NP	#P

Theorem

Consistency checking is in coNP^{NP} for propositional and in $\text{coNP}^{\text{NP}^{\text{NP}}}$ for prob. programs where predicates have a bound on arity.

- Classic negation ($\neg A$), constraints ($:- \phi$), disjunctive heads:

$\text{coloredBy}(V, \text{red}) \vee \text{coloredBy}(V, \text{yellow}) \vee \text{coloredBy}(V, \text{green}) :- \text{vertex}(V).$
 $:- \text{edge}(V, U), \text{coloredBy}(V, C), \text{coloredBy}(U, C).$

Result:

the credal semantics (the set of measures over stable models) of these probabilistic answer set programs is again an infinite monotone credal set.

- Credal semantics is a rather sensible semantics.
- Structure of credal semantics: nicely, infinite monotone Choquet capacities.
- Complexity: partially mapped, still some open questions.